UNC-AM-15-116

ACQUISITION RESEARCH

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Acquisition Risks in a World of Joint Capabilities: Evaluating Complex Configurations

6 July 2015

By

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Prepared for the Naval Postgraduate School, Monterey, CA 93943.

This material is based upon work supported by the
Naval Postgraduate School Acquisition Research Program under Grant No. 00244- 12-1-0047

The research presented in this report was supported by the Acquisition Research Program of the Graduate School of Business & Public Policy at the Naval Postgraduate School.

Abstract

Major Defense Acquisition Programs (MDAP) are becoming increasingly interdependent and complex. Yet, research in the acquisition field has little to offer in terms of how to address the increasing complexity. This research seeks to forge new ground on uncovering early indicators of interdependency acquisition risk so appropriate governance mechanisms can then be isolated. This research examines DoD acquisition from the context of a network of interrelated programs that exchange and share resources for the purpose of establishing joint capabilities. The research focuses on the joint space of major defense acquisition programs; the space where transactions form interdependencies among MDAP programs. For this research, jointness, interdependency, exchange, and partnerships all refer to a similar concept: the notion that autonomous organizations build relationships to obtain resources to provide capabilities that, when looked at in totality, form network structures. Three questions drove the research: to identify whether two specific networks (funding and data) demonstrate preferential attachment, to identify the most frequently occurring configuration patterns, and to determine whether contagion was present and under what conditions contagion was apparent.

Keywords: Major Defense Acquisition Programs, Networks, Network Configurations, Contagion, Exponential Random Graph Models, Preferential Attachment

Abbreviations

DAES – Defense Acquisition Executive Summary

ERGMs – Exponential Random Graph Models

GTD – Graph Theoretic Dimension

K-S – Kologorov-Smirnov

MCMC - Markov Chain Monte Carlo

MDAP – Major Defense Acquisition Program

OSD - Office of the Secretary of Defense

PAUC – Program Acquisition Unit Cost

RDT&E – Research, Development, Test and Evaluation

SAR – Select Acquisition Report

About the Author

Mary Maureen Brown is a Professor of Public Administration at UNC Charlotte and a Senior Fellow at George Washington University Center for Excellence in Public Leadership. Her past experiences include visiting scientist at the Software Engineering Institute at Carnegie Mellon University and three years as chief information officer at the Charlotte Mecklenburg Police Department. Her current research, *Acquisition Risks in a World of Joint Capabilities*, is in its fifth year of sponsorship by USD AT&L. The research involves the identification, design, and development of cost, schedule, and performance risk measures and metrics for major defense acquisition programs engaging in joint capabilities. She is a frequent presenter at the Naval Post Graduate School Acquisition Research Conference.

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Table of Contents

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Introduction

Like most contemporary organizations, the Department of Defense (DoD) is under increasing pressure to reap the synergistic advantages of collaborative efforts. Starting in the early 2000s under former Defense Secretary Donald Rumsfeld, the transformation to a joint warfighting paradigm has been underway now for over a decade. The goals and objectives are well understood and the transformation continues across the armed forces. At its roots is the desire to enhance coordination among sister services, allies, and all levels of government (coalition, federal, state, and local). But, as discussed below, the mechanisms for understanding risk remain underdeveloped.

As a consequence of new defense realities, the integration of capabilities across a range of different MDAPs becomes a crucial factor for success on the battlefield. But, it also widens the number of stakeholders and requirements that must be met. Accommodating joint requirements typically means that fiscal resources will derive from a wider set of sources, with all of the political and financial complexity they portend.

MDAP programs are becoming increasingly interdependent and complex. Yet, research in the acquisition field has little to offer in terms of how to address the increasing complexity. This research seeks to forge new ground on uncovering early indicators of interdependency acquisition risk so appropriate governance mechanisms can then be isolated.

This research examines DoD acquisition from the context of a network of interrelated programs that exchange and share resources for the purpose of establishing joint capabilities. The research focuses on the joint space of major defense acquisition programs (MDAPs): the space where transactions form interdependencies among MDAP programs. The research is especially salient because, to date, little is known about the risks associated with interdependent activities. The potential benefits of the research are substantial. First, all indicators suggest that joint activities within the defense domain will continue to proliferate. Second, not only are joint activities of interest of the U.S., but they are also of interest to our allies. Third, the lessons learned will be applicable to sundry domains.

For this research, jointness, interdependency, exchange, and partnerships all refer to a similar concept: the notion that autonomous organizations build relationships to obtain resources to provide capabilities that, when looked at in totality, form network structures. While it is true that at the individual pair-wise level, these exchanges exist as explicit transactions for the transfer of data, labor, capital, or materials, it is also true that the totality of the various dimensions, coupled with the turbulence of perturbations, influences the cost, schedule, and performance of the acquisition effort.

The primary objective of the research was to isolate how interdependencies influence program performance. Three questions drove the research. The first question was to identify whether two specific networks (funding and data) demonstrate preferential attachment. As discussed further below, preferential attachment occurs when a small number of programs serve as hubs for the network. The presence of preferential attachment is important to program performance because while it can demonstrate greater levels of efficiency, it can also indicate higher levels of vulnerability.

The second question sought to identify the most frequently occurring configuration patterns. Network researchers have identified a number of configurations, with each type suggesting different insights that might influence program performance. The third question focused on determining the extent to which MDAPs in the network(s) experience contagion and under what conditions contagion was apparent. The discussion below begins by providing a short synopsis of network analysis. Once this foundation is established, attention shifts to the research methods. The findings section follows and is organized according to the three research questions. The paper closes with recommendations for continued research on the role of interdependencies on program performance.

Background

Theoretically, the DOD Transformation is about instilling processes and practices that promote knowledge and agility. In short, DoD is looking to Joint Capabilities as a mechanism to expand both the breadth and depth of current understandings, and to facilitate the agility needed to spontaneously leverage a wide range of inter-service, intergovernmental, and inter-national resources. The DoD transformation is about information enabled processes and organizations that are capable of improving the understanding of the battlefield environment. According to Alberts (2003) "agile organizations are masters in not only threat detection and eradication, with the ability to quickly and precisely leverage a wide range of detection and eradication resources dynamically and on-the-fly; but are also distinguished by their proactive use of knowledge and intelligence to initiate anticipatory and preventive actions and strategies to checkmate the enemy before the first bomb is dropped or the first shot fired."

Ideally, joint capabilities should provide significant defense advantages. From the battlefield perspective, joint capabilities should promote greater situational awareness and thus reduce the risk of fratricide (i.e., “friendly fire”). An improved understanding of the location of various Service resources should also allow battlefield commanders to tap a wider range of arsenal assets. From a support perspective, joint capabilities should allow support agencies to improve their understanding of where various resources are located and how to leverage them to assist battlefield operations. Furthermore, from a command perspective, joint capabilities should improve understanding of the available resources that can be leveraged and enable a greater understanding of how to mitigate enemy threats.

While DoD agencies are expected to embrace joint capabilities, research findings on the associated acquisition risks and best practice mechanisms of joint interdependent activities lag far behind (Isett and Provan, 2005). Overall, the study of interdependency and its effects on program performance have yielded too few tangible results (Agranoff and McGuire, 2001).

There are few tested and proven tools for program managers and acquisition executives to employ to assess the joint space, or gauge the cascading consequences, or domino effects, that the joint space might trigger. Thus, as the transformation continues, the acquisition arena has remained largely program centric. Despite the fact that many MDAPs are identified as explicitly joint in their Select Acquisition Reports (SAR), the Defense Acquisition Executive Summary (DAES) process, milestone reviews, and most oversight functions focus on the program entity to the exclusion of the joint space that allows MDAPs to leverage and share resources. In the absence of verifiable research, little attention has been given to the risks of the critical interfaces and interdependencies that underlie the formation of joint capabilities.

The analysis of interconnected programs has typically occurred in one of two ways: either through a system-of-systems / family-of- systems lens or via a supply chain pair-wise lens. Both of these methods suffer from severe conceptual shortfalls. System-of-systems and family-of-systems operate from the context that boundaries can be drawn and defined around the scope of the interconnections. A plot of the critical data interdependencies that MDAP programs exhibit reveals the difficulty and arbitrariness of this type of conceptualization (see figure 1).

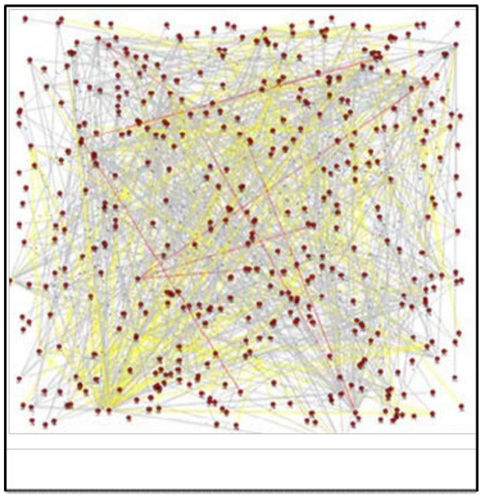


Figure 1: MDAP Interdependencies

The study of interconnections from a supply chain perspective has similar shortfalls. Supply chain perspectives assume that the interconnections are the sum of the individual pairwise connections. Under this conceptualization, as long as each pair (or dyad) is adequately maintained, the entire chain operates smoothly. In reality, many of the interconnections that dominate MDAPs do not fit the system-of-systems / family-of-systems or supply chain analogies. Thus, the lessons learned from these two approaches are unlikely to provide value when programs exhibit joint characteristics.

This research examined MDAP interdependencies as landscapes of overlapping multi-dimensional characteristics that influence behavior. The research examined the MDAPs as landscapes of multiple overlapping interdependencies with first order, second order and *n*- order connections. For this research, jointness, interdependency, exchange, and partnerships all refer to a similar concept: the notion that autonomous organizations build relationships to provide capabilities that, when looked at in totality, form network structures. While it is true that at the individual pair-wise level, these exchanges exist as explicit transactions for the transfer of data, labor, capital, or materials, it is also true that the totality of the various dimensions, coupled with the turbulence of perturbations, influences the cost, schedule, and performance of the acquisition effort. The primary value of the research is that it tested multiple methodological approaches for conceptualizing the interconnections so that new insights could be provided on: 1) how to best measure these increasingly complex approaches to acquisition, 2) understanding of the behaviors they exhibit, and 3) identifying valid risk mitigation governance mechanisms that have a high degree of success. Hence, this research seeks to address the problem that there is an absence of insights on the effects of interdependencies and a lack of tested metrics to provide early indication of the acquisition risks of interdependent programs.

Interdependent Networks

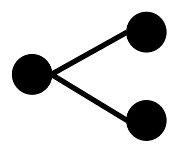
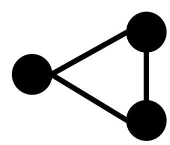
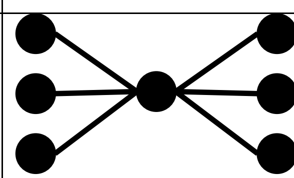
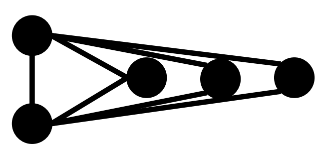
A novice's glance into the field of interdependent organizational-based networks is likely to reveal a terminological jungle of abstract and obscure vocabulary. This section of the report seeks to convey many of the more common network terms and place them in the context of DoD acquisition. Table 1 provides a glossary of several of the key terms. At the onset, it is important to recognize that the term *social* is used in a specific empirical context for understanding programmatic interactions: "social systems of interaction" form the basis from which material equipment and organizational capacities get things done (Turner, 1988).

Wasserman and Faust (1994) defined the social network perspective as a focus on the relationships that exist among entities and the patterns and implications of these relationships. Overall, the vantage point is that

- actors and their actions are viewed as interdependent rather than independent, autonomous units;
- relational ties between actors are channels for the transfer of resources; and
- network models view the structural environment as providing opportunities for, or constraints on, individual and collective action (Wasserman & Faust, 1994, pp. 3–4).

In the work setting, network actors (or nodes) often represent people, teams, or organizations. A tie represents some form of interaction or relationship. In short, network structures provide the "plumbing" for the flow of resources through the network. Interdependent networks are complicated by the fact that they are multidimensional, and as such, understanding their behavior requires consideration of multiple levels of analysis. Typically, networks can be characterized in light of four basic levels: the individual, the subnetwork(s), the entire network, or as a multiplex network. A multiplex perspective considers the node from a multi-network consideration.

Table 1: Terms and Configurations	
Terms	
Edge	A tie or link between two nodes
Ego	The focal node or actor
Alter	The neighbor of ego
Reciprocity	The ratio of (the number of links which are the part of reciprocated relations) to (the total number of links)
Density*	The proportion of ties to the number of all possible ties

Diameter	The length of the longest path between connected actors in a network
Betweenness Centrality*	A measure of the extent to which a node lies between all pairs of nodes on the geodesic path.. tells us which people are most “between” other people. Can be used to reflect brokerage.
Closeness Centrality*	The degree to which a given node is near or close to all of the other nodes.
Degree Centrality*	Total number of edges for a given node; In-degree represents total number of in bound edges Out-degree represents total number of out bound edges
* May be measured in light of each individual actor or ego or as an average for the entire network	
Undirected Network Configurations (Directed has Arrowheads)	
2-Stars Often indicates popularity or preferential attachment	
Triangle – indicates closure among partners	
Alternating k-Stars Indicative of the activity of actors to engage others.	
Alternating-Triangle Can indicate tightly coupled closed relationships or Path Closure	

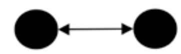
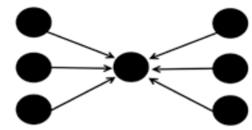
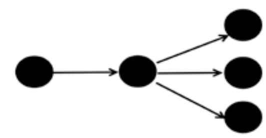
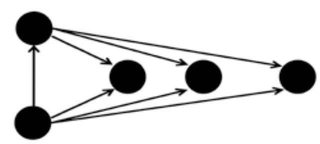
Reciprocity – indicative a two-way relationship	
Alternating In Star – indicative of popularity or hub	
1 In Alternating Out Star – indicative of diffusion	
Alternating Triangle Upward – indicative of tight closed clustering	

Table 1 provides definitions for the most common network terms. At the individual (or node) level, an ego is the central node of interest, and those connected to the ego are known as alters (see Figure 2a). A network rendering from the context of an ego is referred to as an ego-network. A dyad consists of an ego and its adjacent alter. As discussed further below, examining data in light of the dyads (or pairs) provides the ability to test the influence that one node might have on another.

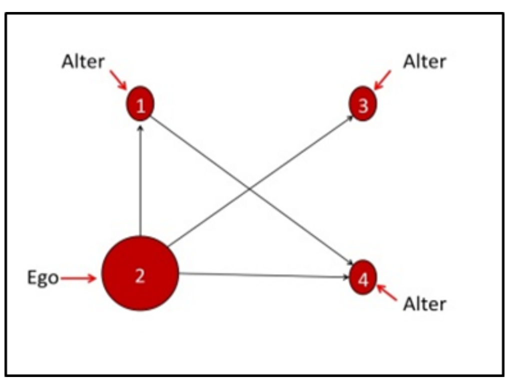


Figure 2a Ego Network

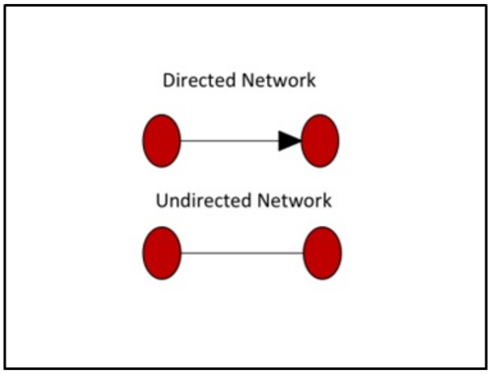


Figure 2b Directed versus
Undirected Graph

A directed network is one where the flow of resources moves in a specific direction, either inbound to an ego or outbound from an ego (see Figure 2b). For example, the data-sharing network identified previously is a directed network because the data flow from one program to another. A directed network can be either sequential or reciprocal in nature. Figure 2c illustrates several descriptive statistics that are commonly discussed. A node is labeled as a broker when it connects two distinct subnetworks. Per Figure 2d, Program Number 554 (Multifunctional Information Distribution System Joint Tactical Radio System), acts as a broker between three subnetworks. An isolate is a node with no ties. Again, in Figure 2d, Program Number 419 (EA 6B Prowler) is an isolate. In directed networks, a node can serve as a transmitter, a receiver, or a carrier. A bridge is identified when a tie spans two subnetworks.

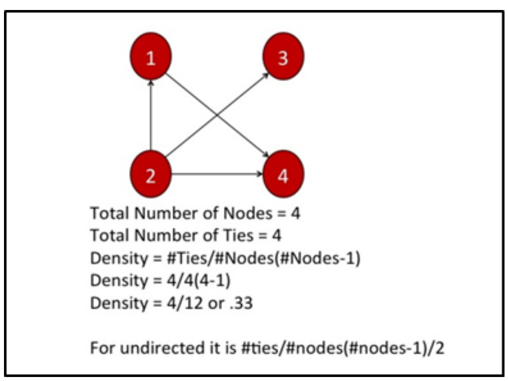


Figure 2c Network Descriptive
Statistics

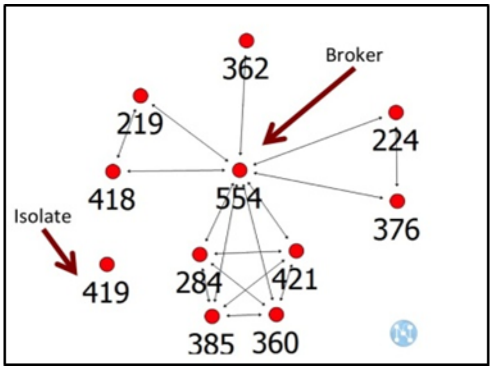


Figure 2d Network Broker

Relying on matrix algebra, a number of metrics have been devised throughout the years to measure networks. Some of the metrics occur at the node or ego level, and others are at the subnetwork or whole-network levels. Nodes are often considered in light of their position, or role, in the network. These ego-level metrics are calculated relative to others in the network.

The degree of a node is the number of ties that a node exhibits. These ties can be measured as inbound or outbound (or both) in a directed network. Another measure is the geodesic distance that one node may be from another. Adjacency identifies direct connections while reachability identifies whether any two nodes are capable of connecting by way of other nodes. Degree centrality identifies the number of ties that a node possesses. The more ties relative to others, the greater the centrality. Closeness, on the other hand, indicates how close a given node is to the remaining nodes. When all of the nodes are close to all of the other nodes, the interaction level among the nodes is typically high.

Network size is often calculated as the sum of the number of nodes or number of ties. Networks are often measured by the longest, or shortest, path between two nodes. The bridge identified previously is often of interest because it indicates that if the tie between the two nodes can be cut, the network can be disconnected or reduced to its subnetworks. The same holds true for the broker. If a broker is eliminated, the network will be reduced to a number of subnetworks. Node connectivity identifies the minimum number of nodes that have to be removed to disconnect the network. “Betweenness” is the extent to which a given node lies between other nodes and, thus, could act to facilitate or block the flow of resources.

“Density” refers to the proportion of ties relative to the absolute total. “Relational embeddedness” refers to the quality and depth of a single dyadic tie. “Structural embeddedness” refers to the extent to which a node’s alters are connected to each other. Because structural embeddedness reflects the degree of the interactions, it is often used as a proxy for understanding network actions.

In the study of networks, scholars often take either a structural or a connectionist approach. Structural approaches examine the structure of the network and its influence on key variables of interest. Connectionists, on the other hand, focus on the flows between the nodes. Those who study social capital tend to focus on the possibilities of actions that social ties provide. Others, however, tend to be more concerned with diffusion and the dynamics of network change over time. Still, other studies focus on why and how networks develop, how and why they change over time, and finally, what influences they exert. Social capital is mostly studied at the individual level, and diffusion is observed from the perspective of the entire network.

Studies of the influence of dyadic ties on performance have mixed and contradictory findings. For example, Perry-Smith and Shalley (2003) found that weak ties led to creativity, but others claim that strong ties are more advantageous (Sosa, 2011). Others claim that it is not the number of ties but rather the depth of the engagement that matters. No one would be surprised by the idea that, relative to fewer ties, more ties may provide organizations with better information that might promote enhanced decision-making. At the same time, information overload and difficulties with scrubbing data to provide information at the proper specification level has become a real problem for many managers.

Similarly, studies of embeddedness are equally contradictory. According to some, the more each node knows about the others, the more constraints there are on each other's behaviors. This is often seen as a positive. Parties gather information on whom to avoid as well as potential opportunities and synergies. Structural embeddedness allows the use of sanctions since knowledge of misfeasance influences reputational value. But these constraints can backfire and actually restrict flexibility. Too much embeddedness can also create problems. It can lead to feuding, group think, and welfare support of weak members. Social aspects such as restricting access to exchanges, imposing collective sanctions, and making use of social memory and cultural processes all influence nodal behavior. Apparently, networks and ties matter, but the extent of the influence is highly debatable.

Much of the incongruity in the findings may be due to the difficulties associated with measurement and data collection. Researchers are challenged by the burden of the data collection requirements, and organizations are often frustrated by the extent of the data request. Because multilevel data are needed for each specific relationship, the data collection task can be onerous. Moreover, given that the study of networks is a fairly new phenomenon, typical organizational records often lack insights at a network level.

Despite these contradictory findings and data collection difficulties, the examination of networks and ties that manifest as interdependencies is likely to provide substantial insights into a number of issues. First, when considering cost and affordability, examining a program in isolation of the entire value chain is likely to provide erroneous information. Second, a wealth of research illustrates the importance of risk management. Considering the risks of a given program without considering its interdependencies may underestimate the true risk level. Next, in the decision of a start-up or termination, it is essential to know how the inclusion or removal of a program will influence its n-order neighbors. Finally, network conditions may exert powerful influences over program sustainability. The following discussion explores the methods used to conduct the research, after which the funding and data networks that manifest the acquisition arena are explored.

Data and Methods

The sample for the research consists of all active Major Defense Acquisition Programs between the 2005-2012 time-period. FY2005 was identified as the beginning year because prior to this period, data were not automated in a way that allowed statistical analysis of networks. Per DoD directive number 5000.02, an MDAP is an acquisition program that is estimated to require an eventual total expenditure for Research, Development, Test and Evaluation (RDT&E) of more than 365 million in Fiscal Year (FY) 2000 constant dollars or, for procurement, of more than 2.19 billion in FY 2000 constant dollars. Given their high cost, DoD provides annual reports to Congress on MDAP performance in what is termed as a Select Acquisition Report (SAR). Annual SARs provided the data analyzed in this study. Within these reports DoD provides insights on the program's cost, schedule, and performance for the given year. The report also provides the account number(s) of the funds that served to finance the program. These account numbers are referred to as "program elements" or PEs. Hence the study below is based on fiscal interdependencies that exist among the MDAPs. The assumption is that collaborative efforts would entail and exchange of monetary resources and that would be realized by examination of the funding interdependencies.

As mentioned, the sample is all active MDAPs between 2005 and 2012. Two important distinctions require clarification. First, the study below is based on only those accounts that are employed for "research, development, testing, and evaluation (RDT&E)." DoD discriminates between accounts that are employed for procurement and those that fund RDT&E activities. Given the vagaries of the two types of money, the study below examines only those accounts that refer to RDT&E funds. The second clarification is that SARs are not published during those years when a new president has taken office. As a consequence, where the study examines the 2005-2012 time period, no SAR was published for FY2008. Hence, the study is restricted to RDT&E accounts for seven years spanning the eight fiscal years 2005 through 2012.

The data interdependencies were derived from an Office of the Secretary of Defense call for information from MDAP program managers in 2010. In 2010 managers were surveyed to determine the critical data interdependencies that existed among the MDAP programs. The program managers identified the inbound and outbound critical data connections. Interviews with OSD employees indicate that because the interdependencies were tied to initial requirements, they were assumed to be static. Meaning that the connections do not vary over time. These data were then merged with the SAR data.

Descriptive Statistics of the Funding and Data Networks

The descriptive statistics of the funding and data networks is provided below. Per above, in the organizational arena, interdependencies can be viewed in three ways. As Thompson (1967) illustrates, network arrangements can be pooled, sequential, or reciprocal. Under a pooled arrangement, network actors draw down from a common pool of resources. Under this scenario, the actors do not interrelate, but they are nonetheless interdependent because they all share a common resource that can be depleted. The funding interdependencies described below reflect a pooled relationship. These acquisition programs share a common program element. Thus the interconnections reflect their interdependencies on a common funding source.

Sequential relationships are often termed supply chains. In these scenarios resources flow in a sequential manner from program to program. Reciprocal relationships are often seen as the most complex and have the greatest risk. In this case, resources are exchanged and as a consequence there is a two-way link among the programs.

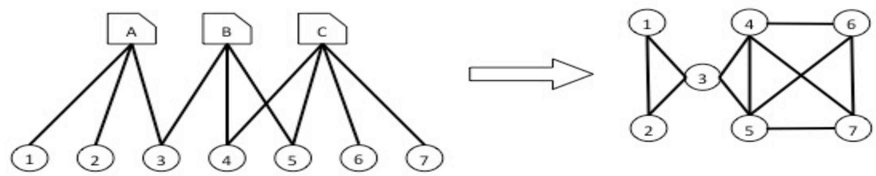


Figure 3: Bipartite Graph Conversion

When network configurations are pooled in nature (bipartite), they are often converted into a one-mode network so the object of interest can be analyzed in closer detail. A bipartite network is one where the nodes are seperated into two unconnected sets. An example of this type of network would be individuals attending events. In this case, the bipartite network is made up of one set of MDAPs and one set of PEs or accounts. Bipartite networks are often converted to undirected networks for analysis purposes. Figure 3 provides a rendering of how the conversion occurs. The conversion is especially appropriate in the event that the central question rests on one set of nodes as is the case in this specific study. Consequently, for each year, the MDAP to PE account network was converted to an undirected network to examine connections among the MDAPs in light of shared accounts.

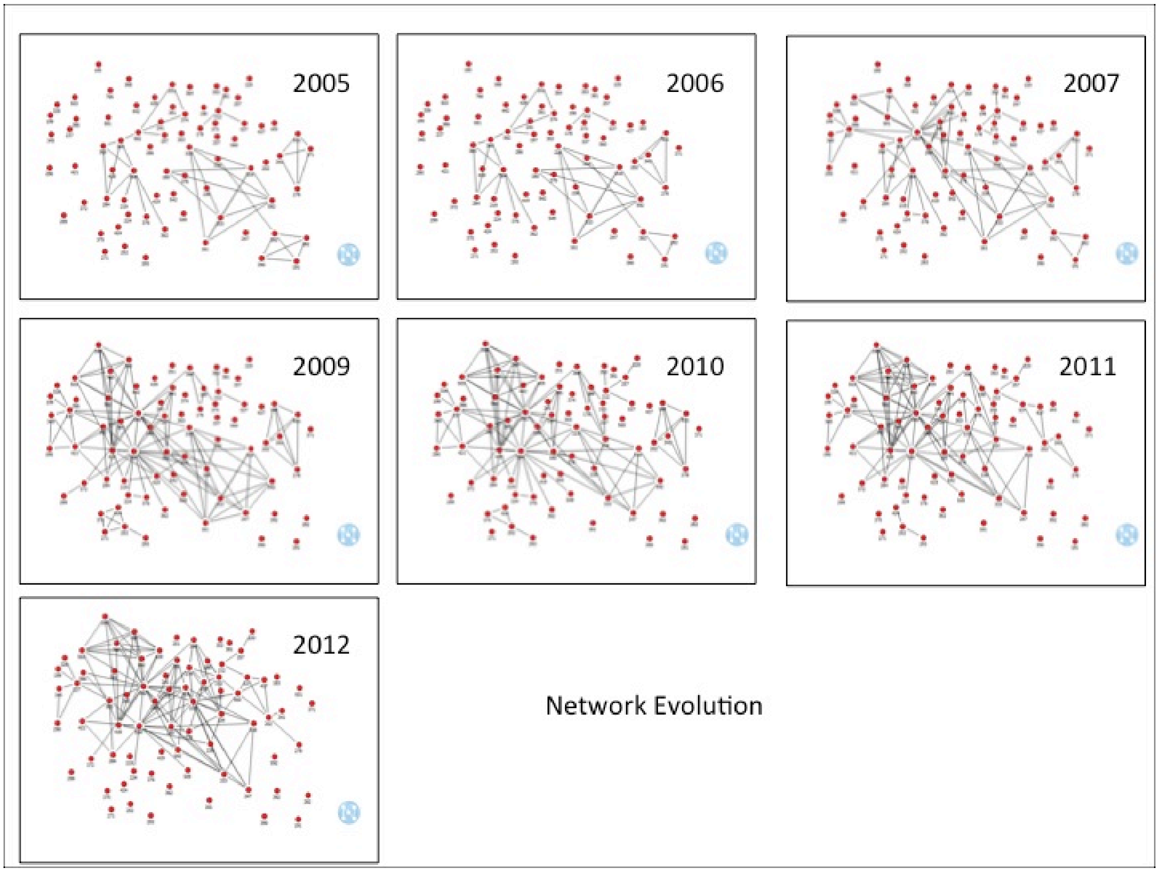


Figure 4: Fiscal interdependencies by year

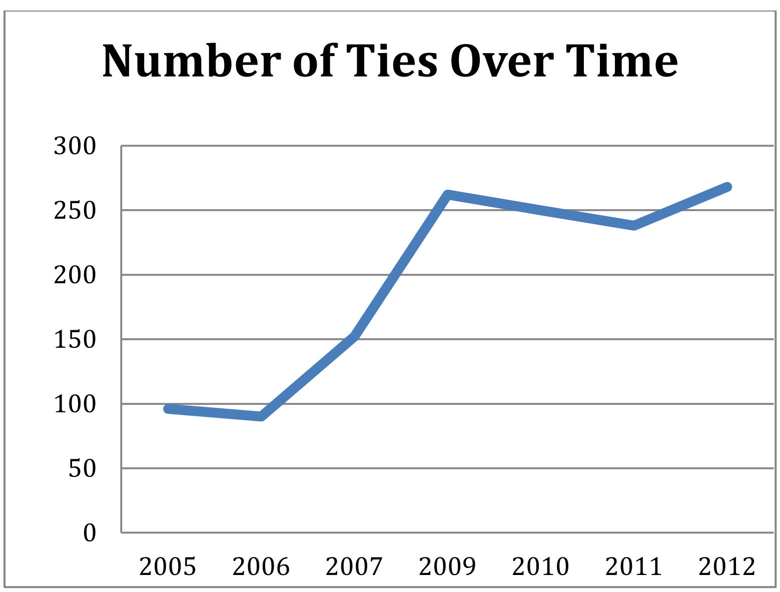


Figure 5: Number of Ties over Years

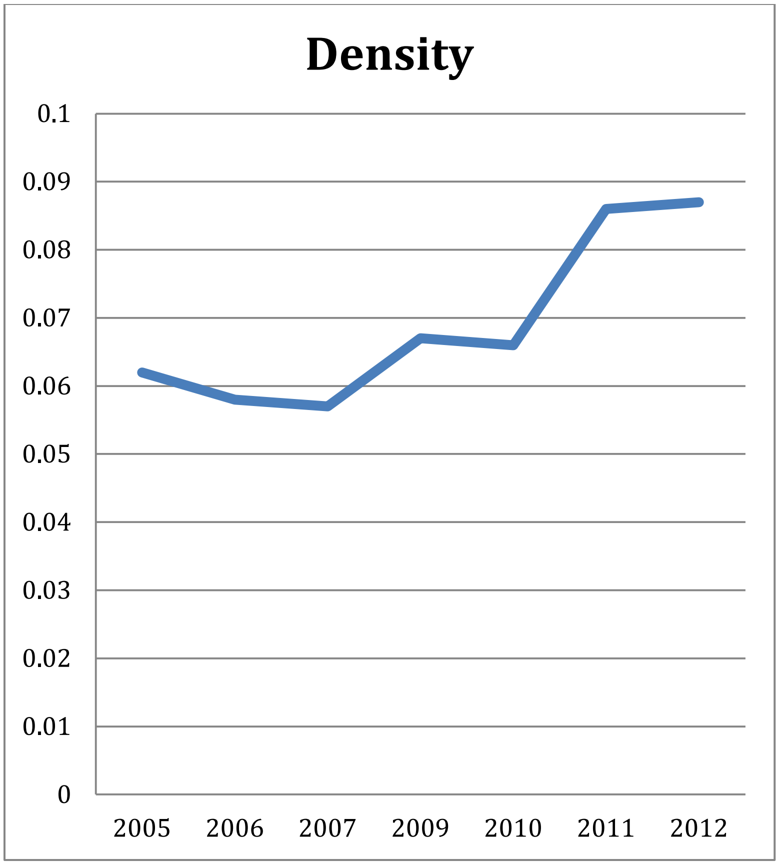


Figure 6: Density Changes over the Years

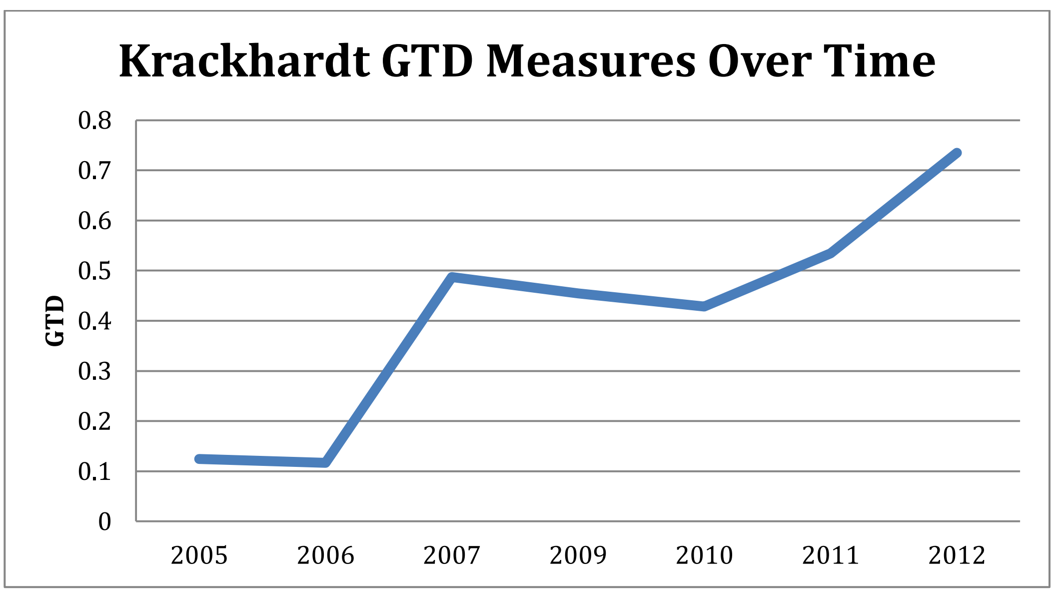


Figure 7: Krackhardt GTD Measures Over

Figure 4 displays the funding interdependencies and how they grew over time. As displayed in the figure, the interdependencies have grown increasing complex over time. The density has grown from a low of 6 percent to a high of 22 percent. Previous work has shown that in a growing network there is a critical probability (termed the “percolation threshold”) where the network structure changes from a loose collection of small clusters to a system dominated by a single giant component. The giant component is a connected, isolated subnetwork where every node is reachable from most any other node. The presence of a giant component is suggestive of emergent order and complexity. As illustrated in Figure 5, the financial network illustrated a growing number of ties that peaked in FY 2009. Yet, per Figure 6, the density has continued to grow through the years. The Krackhardt Graph Theoretic Dimension (GTD) measures identify the amount of hierarchy in an informal network. A hierarchically nested structure indicates that smaller groups are embedded in larger groups. The Krackhardt GTD ranges from zero to one where one indicates that every node in the network can reach every other node. Per Figure 7, in 2005 the Krackhardt GTD was only 0.12 but by FY 2012 it had grown to 0.75. Not surprisingly, at the same time, the compactedness of the network also increased (See Figure 8).

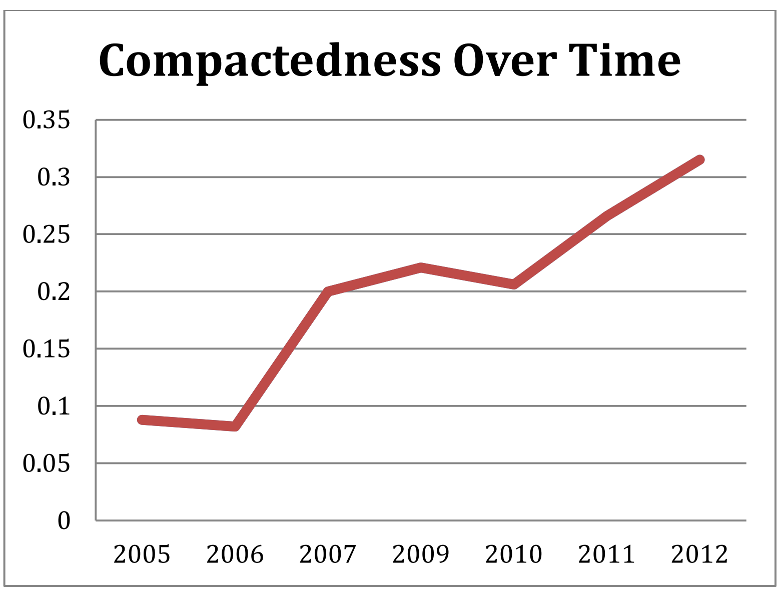


Figure 8: Compactedness Changes over

As mentioned, the data interdependencies do not vary over time. The data interdependencies are reciprocal in nature – they are directional (inbound or outbound) connections. Figure 3 illustrates the data interdependencies. As demonstrated in the diagram, these interdependencies reflect 326 ties and range from 27 percent inbound to 16 percent outbound. The Krackhardt Graph Theoretic Dimension (GTD) is static at 0.37.

Table 2: Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Recovery Rate	26	1.00	5.00	2.08	1.09
PCT PAUC Growth FY 2012	48	-32.35	12.89	-1.17	6.31
PCT PAUC Growth FY 2011	46	-19.92	167.83	3.19	25.63
PCT PAUC Growth FY 2010	45	-7.55	17.75	1.75	4.81
PCT PAUC Growth FY 2009	42	-38.37	69.80	5.07	18.09
PCT PAUC Growth FY 2007	37	-13.28	44.84	2.04	8.98
PCT PAUC Growth FY 2006	36	-4.24	17.39	1.91	4.55
PCT PAUC Growth FY 2005	32	-19.57	9.61	-0.36	4.63
Total Cost Variance FY2005 ($M)	48	-1199.70	427.60	2.25	201.33
Total Cost Variance FY2006 ($M)	48	-341.00	437.60	18.64	128.74
Total Cost Variance FY2007 ($M)	48	-146.90	909.70	29.99	140.46
Total Cost Variance FY2009 ($M)	48	-39.80	5798.20	197.75	841.84
Total Cost Variance FY2010 ($M)	48	-49.10	4228.60	196.85	640.34
Total Cost Variance FY2011 ($M)	48	-318.30	837.10	42.42	185.13
Total Cost Variance FY2012 ($M)	48	-184.00	431.10	19.42	85.06
Number Years with Positive PAUC Growth Between FY2005-FY2012	48	0.00	6.00	2.65	1.91
Average Number of Funding Partners Per Year	74	0.67	15.00	3.50	2.46
Average Number of Data Partners	65	1.00	15.00	5.02	4.22

A few other interesting findings are reported in Table 2. PAUC growth was measured as the percent growth from the previous year. Per the table, average annual growth ranged from a high of five percent to a low of minus one percent. Cost variance was highest in FY2009 and FY2010 coming in with a mean of approximately $200M. The average recovery rate, or the average amount of time a program illustrates positive PAUC growth before returning to a zero of negative growth rate, was roughly two years. For the FY2005-2012 time period, the average number of years with positive PAUC growth was two and one-half. MDAPs averaged three and one-half partners over the time period and the in the data network they averaged five partners.

The Question of Preferential Attachment

The subject of preferential attachment has received important attention over the past five years. First isolated by Barabasi and Albert (1999), preferential attachment refers to the notion that the more connected a node, the more likely it is to recive additional connections (sometimes referred to as "the rich get richer" phenenomen). Preferential attachment follows a power-law distribution. Preferential attachment has important implications for networks because, on the one hand, they illustrate efficiency precisely according to a lack of redundancy in the web of nodes. Yet, on the other hand, they exhibit increased vulnerability owing to a lack of redundancy. In short, network operations are vulnerable to the healthiness of the most highly-connected nodes. Hence the presence or absence of preferential attachment could be indicative of the overall well being of the network.

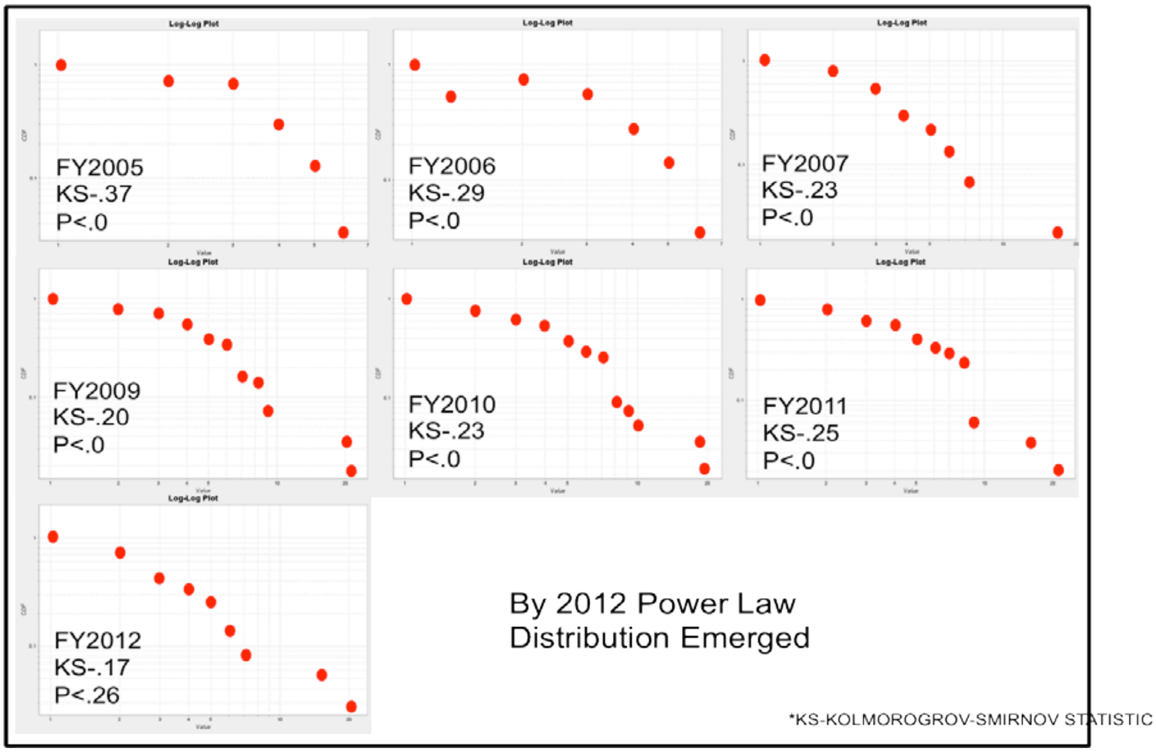


Figure 9: Preferential Attachment Over

To test for preferential attachment, the Kolmogorov-Smirnov (K-S) and goodness-of-fit tests were obtained. The K-S statistic tests whether the distribution is significantly different from a power-law distribution. When the p-value is signifcantly larger than .1 it can be assumed that the data distribution does not differ from a power-law distribution (Clauset et al, 2009). Per figure 9, years 2007-2011 failed to confirm the power law distribution. However, FY 2012 did yield a power law distribution. Hence, preferential attachment was demononstrated in FY 2012. Given the results of the examination of the topological structure and the occurrence of preferential attachment, the findings illustrate spontaneous emergence of order at about the FY2009 time period that resulted in much greater network complexity by 2012.

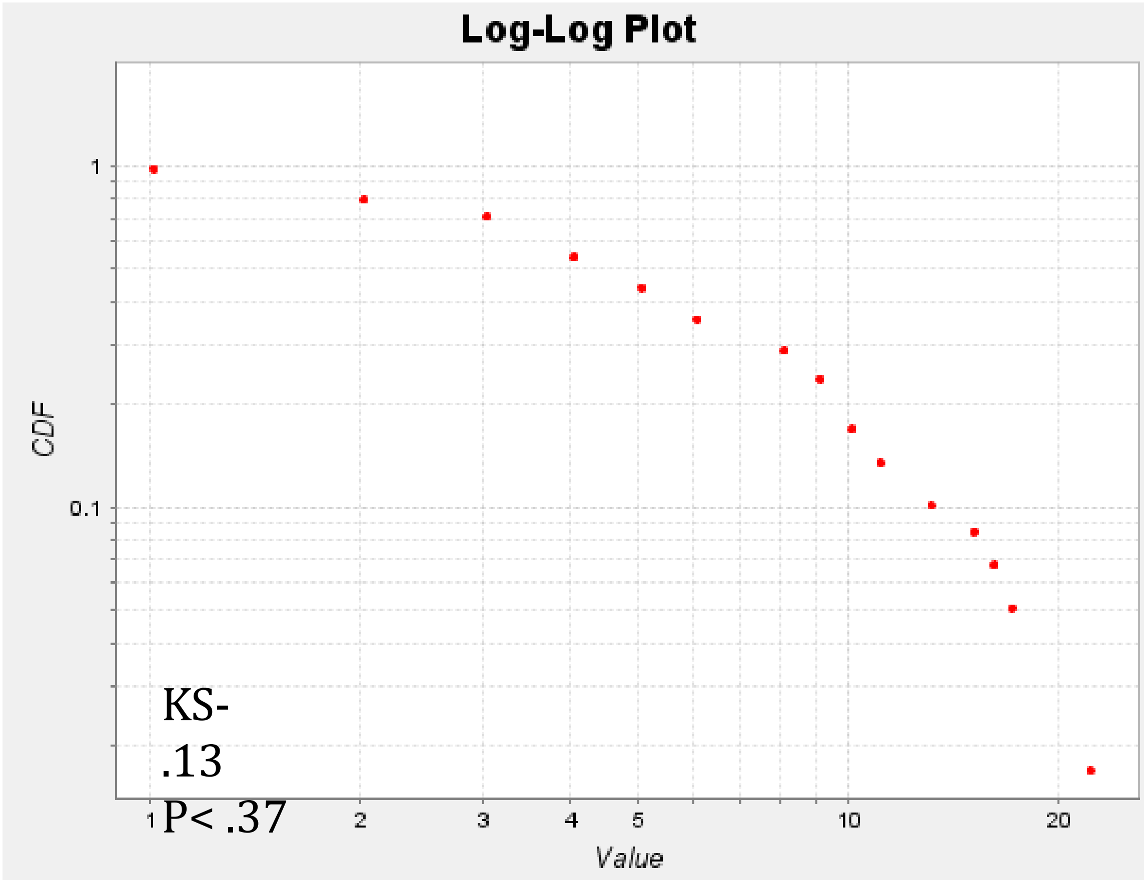


Figure 10: Preferential Attachment of Data Interdependencies

Figure 10 provides a rendering of the power law distributions. In terms of the data network, preferential attachment was also demonstrated with a KS statistic of 0.13 (p<.37). In short, both networks exhibit preferential attachment with a small number of MDAPs illustrating an unusually high number of partners.

The Question of Complex Configurations

To test whether the MDAPs experienced any rare, or significant, configurations, exponential random graph models (ERGMs) were employed. Over the past several decades researchers have sought statistical techniques that would allow inferential examination of networks. In the recent past, several refinements to previously established algorithms has led to ERGM development. ERGMs collectively constitute a family of models that offer wide application to a variety of network structures. In short, ERGMs take the form of a probability distribution, enabling one to model a given network as a single multivariate observation. ERGMs are employed as an effective way to investigate social networks owing to their ability to posit various alternative configurations, and test whether their occurrence is statistically different from the norm (Shumate and Palazzolo, 2010).

The central problem in employing standard statistical techniques in network analysis is the lack of independence among the actors and their ties. ERGMs are more effective than standard techniques for studying networks in that they control for interdependence by explicitly modeling it in the equation. Table 1 provides key terms and the configurations tested below. Per Table 1, networks can be examined in light of various configurations that range from simple dyads to complex triangles. In the ERGM model, each parameter corresponds to a configuration in the network and represents a distribution of random graphs (Pattison and Robins, 2002).

With ERGMs different network configurations can be hypothesized (i.e. reciprocity / exchange, triadic closure / transitivity, preferential attachment) and then statistically tested without risk of violating the independence assumption. ERGMs are powerful in that they model the conditional probability of a tie, or configuration, given the entire network. In their most basic form, in predicting a tie from *i* to *j* ERGMs take the expression: $P(X_{ij} = 1 | X_{-ij} = x_{-ij}, \theta)$ where the probability of a tie occurring between two nodes in a network (X) is conditionally dependent on the presence or absence of a tie in the observed network (x) (Snijders et al, 2006).

ERGMs are capable of incorporating three dependency structures. Dyadic dependence captures the presence of reciprocity between two nodes. Markov dependence goes a bit further in that two potential ties are assumed to be conditionally dependent if they share a common actor. Over time, researchers found that the Markov assumption was too restrictive and led to poorly fitting models. Thus, refinements were offered by Pattison and Robbins (2002) and Snijders et. al (2006). The new form is based on partial conditional independence. In other words, two potential ties are considered to be partial conditionally dependent if: 1) they share a common actor, and 2) if two ties exist they are part of a four-cycle configuration.

So, employing the joint form of the model, a probability distribution expression for all tie variables is taken from Koskinen and Daraganova (2013):

$$\Pr(X = x) \,|\theta \equiv \frac{1}{\kappa(\theta)} \exp\{\theta_{\mathrm{l}} z_{\mathrm{l}}(x) + \theta_2 z_2(x) + \ldots + \theta_{\mathrm{p}} z_{\mathrm{p}}(x)\}$$

Per standard statistical tests, a parameter estimate greater than two times the standard error is deemed a significant effect, *given the other parameters in the model*. In some ways, ERGMs are similar to logistic regression in that they cannot indicate the strength of the relationship but rather indicate the probability of occurrence. It should be noted that the configurations are added to the model sequentially starting with a simple arc and traversing to more complex relationships. The sequential addition prevents the occurrence of double counting ties.

As alluded to above, the parameter estimate reflects the probability of a given network configuration or nodal attribute. ERGMs make use of Markov Chain Monte Carlo (MCMC) to simulate a distribution of networks (Koskinen and Snijders, 2013). Each simulated network is compared to the original observed network. Starting with an empty network, the algorithm iterates thru the generation / compare process based on the number of updates identified by the researcher. The chain is said to have “converged” when estimates stabilize, in other words when the convergence statistics are 0.1 or less. A lack of convergence suggests that the model is poorly specified. Once the sample is established, parameter values are derived via maximum likelihood estimation (MLE). The MLE technique involves evaluating the probability over all possible networks of the same size as the observed network. MCMCMLE is a longstanding simulation approach for complex stochastic systems (Valente, 2010).

Shumate and Palazzolo (2010) argue that ERGMs offer superior capabilities over and above earlier models because they are capable of accommodating a wide range of network configurations, they can handle skewed bimodal distributions, and they have a high tolerance for collinearity. As a consequence they argue that ERGMs represent a promising class of models for those interested in social network analysis. As indicated above, ERGMs provide the ability to test whether a given network illustrates configurations that are out of the norm for what would be normally expected.

Table 1 provides an illustration of the various network configurations that were tested. In short, stars illustrate popularity or preferential attachment. Triangles indicate a predisposition for closure. Alternating triangles show tightly coupled relations.

Table 3: ERGM Results Funding Interdependencies (Undirected Network)					
	FY2007	FY2009	FY2010	FY2011	FY2012
2-star	0.23	0.01	-0.06	-0.15*	-0.12*
3-star	-0.01	0.00	0.01	0.01*	0.01*
Triangle	0.53	0.49*	0.62*	0.72*	0.65*
Alternating Star	-2.38*	-1.89*	-1.66*	-1.29*	-1.12*
Alternating Triangle	1.43*	2.03*	1.83*	1.33*	1.50*
* p<.05					

Table 4: ERGM Results Data Interdependencies (Directed Network)	
Parameter	Coefficient
Arc (intercept)	-4.44*
Reciprocity	4.02*
Alternating In Star	0.97*
1 In Alternating Out Star	-0.62*
Alternating Triangle Upward	0.64*

The coefficients of the ERGM analyses are provided in Tables 3 and 4. ERGM analyses were not obtained for FY2005 and 2006 because the fragmented nature of the network prevented model convergence. It was not until FY2007 that the network demonstrated enough structure to test for the significance of different topological structures. As mentioned, ERGMs employ MCMC maximum likelihood estimations. All models demonstrated convergence at a t-ratio of at least 0.1.

The findings of the alternating-stars and alternating-triangles, did illustrate deviation from expectations. Fewer numbers of alternating-stars were revealed in the early years but the sign of the coefficient shifted to positive in FY2012. The alternating-triangles were consistently positive over the span of all of the years. Thus, by FY2012, the network experienced higher numbers of alternating-stars and alternating-triangles than would be normally expected in a network of this size. The high number of alternating-star and triangles are in keeping with a preference for forming cohesive, interlocking relationships.

ERGM analyses of the data interdependencies also revealed several statistical relationships. The arc parameter reflects the intercept. Reciprocity is a measure of the extent to which MDAPs exchange data. The parameter of 4.02 indicates that the data network is four times more likely to exchange data with partners than would normally be expected of a network of this size. The alternating in star demonstrates that the data network experiences roughly .97 more in star configurations that would normally be expected. Not surprisingly, the out star configurations are roughly 0.61 times less likely. Finally, the AT-U is significant with a parameter of 0.64 indicating that there is a preference for tight closed relationships.

Contagion

Complex contagion theories seek to describe networks in terms of the presence of absence of infectious attitudes or behaviors. Contact among the nodes serves as the exposure mechanism. Relying on the models developed by epidemiologists, recent research has begun to examine the potential contagious influence of social behaviors and attitudes among partners in a network. Where "groupthink" is a well-known and common phenomena, few studies have examined social contagion in the work setting. The question of contagion is especially intriguing when partnerships exist over time. While the literature is lacking in the consideration of contagion at a single point in time, very studies have examined its influence over time. Whether long lasting partnerships exhibit the same contagion influences as newly developed partnerships is unknown. In other words, the question of whether the actors reach an equilibrium and, thus are no longer susceptible to their long term partner may have important organizational implications. A recent study by Jordan et al (2013) examined the influence of contagion in cooperative networks. In their study they examined both dynamic and static networks. Their findings suggest that "cooperation can spread from person to person in fixed social networks. And that it it may be possible for interventions to create cascades of cooperation" (p.7).

The analysis of the contagion effects was based on the models provided by Christakis and Fowler (2007).

Let:

1. $Y_i(t)$ and $Y_{\mathrm{i}}(t+1)$ denote the ego's outcomes (Pct PAUC Growth) at time t and t+1, respectively;

2. $Y_k(\mathrm{t})$ and $Y_k(\mathrm{t}+1)$ denote the alter's outcome (Pct PAUC Growth) at time t and t+1, respectively;

3. $Z_i(t+1)$ denote the ego's covariates at time t.

Table 5: Contagion in Funding Networks

	Unstandardized Coefficients	Standardized Coefficients
	B	Beta
(Constant)	-1.07	
Lagged PCT PAUC Growth of Alter	-0.078	-0.067
Lagged PCT PAUC Growth of Ego	-0.058	-0.049
PCT PAUC Growth of Ego	0.027	0.027
Number of Partners	0.321	0.16***
p<.05* p<.01** p<.00***		

Table 6: Contagion in Data Networks		
	Unstandardized Coefficients	Standardized Coefficients
	B	Beta
(Constant)	0.252	
Lagged PCT PAUC Growth of Alter	0.083***	0.084
Lagged PCT PAUC Growth of Ego	-0.003	-0.003
PCT PAUC Growth of Ego	0.057*	0.065
p<.05* p<.01** p<.00***		

Christakis and Fowler regressed $Y_i(t+1)$ on $Y_i(t)$, $Y_k(t)$, $Y_k(t+1)$, and $Z_i(t+1)$ using linear regression. The coefficient for $Y_k(t+1)$ on $Y_i(t+1)$ is interpreted as the contagion effect. Tables 5 and 6 provide the results of the test for contagion. Per table 5, the funding network did not illustrate contagion in light of the MDAP's partners. However, the number of partner's does appear to influence percent PAUC growth. Alternatively, contagion was witnessed in the data network. As shown in table 6, the contagion variable achieved statistical significance.

Conclusion

The primary objective of this research was to isolate how interdependencies influence program performance. Three questions drove the research. The first question was to identify whether the two networks (funding and data) demonstrate preferential attachment. As discussed further below, preferential attachment occurs a small number of programs serve as hubs for the network. The presence of preferential attachment is important to program performance because while it can demonstrate greater levels of efficiency, it can also indicate higher levels of vulnerability.

The second question sought to identify the most frequently occurring configuration patterns. Network researchers have identified a series of configurations, each type suggestive of different insights that might influence program performance. The third question focused on determining the extent to which MDAPs in the network(s) experienced contagion and under what conditions contagion was apparent.

In sum, the funding network demonstrated increased complexity over the years. Preferential attachment was witnessed, as were a high number of stars and triangles. Contagion was not demonstrated, but the number of partners does appear to influence percent PAUC growth.

The data network was a static network. It too illustrated preferential attachment along with an unusually high amount of reciprocity, inbound stars, and triangles. Contagion was apparent and statistically significant. In sum, this research illustrates the important role that interdependencies play on program performance. Based on these results, additional research on the role (and risk) of interdependencies is clearly warranted.

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